IS-286

THE DIAGNOSTICS AND THE FAULT DETECTION OF GAS TURBINE ENGINES BY USING DIFFERENT NEURAL NETWORKS

Giovanni TORELLA
ITALIAN AIR FORCE ACADEMY
81031 Pozzuoli Napoli ITALIA

Roberto TORELLA
The Second University Of Naples
80078 Aversa Caserta ITALIA

XIV ISABE
Fourteenth International Symposium on Airbreathing Engines
September 5-10 1999, Florence ITALY

ISABE 99-7282

THE DIAGNOSTICS AND THE FAULT DETECTION OF GAS TURBINE ENGINES BY USING DIFFERENT NEURAL NETWORKS[1]

Giovanni TORELLA+ Roberto TORELLA^
+Italian Air Force Academy 80078 Pozzuoli Napoli Italia
^The Second University of Naples 81031 Aversa Napoli Italia

Abstract

This paper deals with the results of a research carried out for the evaluation of Neural Networks for engine diagnostics.

The study continues the works made in the past on the same subject. Now the main aim is to find new methods for improving the effectiveness of Neural Nets.

The results presented here concern with two different Neural Nets: the Back Propagation Neural Networks (BPNN) and the Adaptive Resonance Theory Neural Networks (ART1-2).

As regarding BPNN particular attention is paid to the improvement of training time and their robustness.

The study of ART1-2 considers the use and the insertion of the probability of fault happening in the training patterns.

The paper shows in full details all activities carried out as well as all improvements with respect to past results.

1.-INTRODUCTION

The management of aircraft engines during their utilization depend upon several activities. Engine Condition Monitoring techniques control engine health and allow early intervention assuring necessary security margins.

By permitting the maintenance only when it is necessary, diagnostics avoid unnecessary and expensive engine stops and save economical resources.

Obviously right information about engine behaviour makes possible effective diagnostics. More information is available more reliable and useful the results of diagnostics are.

Unfortunately, sometimes during the engine operating life, the causes of engine malfunction and the right interventions must be detected by poor information. Infact it is not possible to have all values of temperature and pressure in any engine section or to know all performance parameters. Moreover the values used for diagnostics may be either approximate or, at the worst, wrong. Anyway diagnostics must proceed and maintenance must start.

Owing to its inherent characteristics Neural Networks may effectively support engine diagnostics.

Neural Networks are information processing systems imitating biological Neural Nets (1). Fig. 1-2 show the work done by the Nature and by the researchers respectively. The wonderful image in fig. 1 comes from ref. 1.

Elemental units, called neurons, form the Nets and the different arrangements of neurons define a particular Neural Network.

Neural Networks are useful for many tasks such as: classification, clustering and recognition of patterns, (1), (2), (3), (4). Moreover they work satisfactorily also with poor and inaccurate information. This feature makes Neural Networks particularly suitable for activities linked to engine maintenance (5), (6), (7), (8), (9), (10).

This paper deals with the recent activities carried out for developing, testing and using Neural Networks for engine diagnostics.

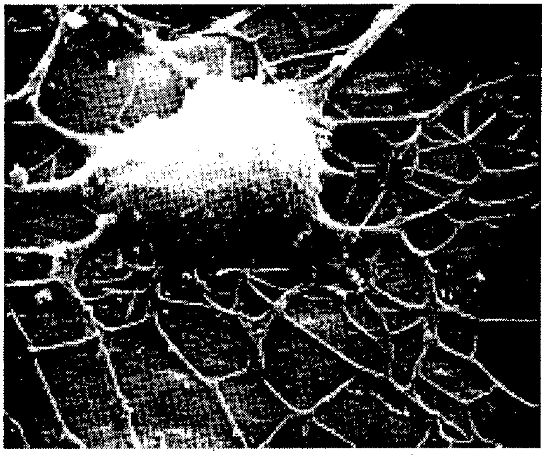


Fig. 1 The wonderful image of a human neuron

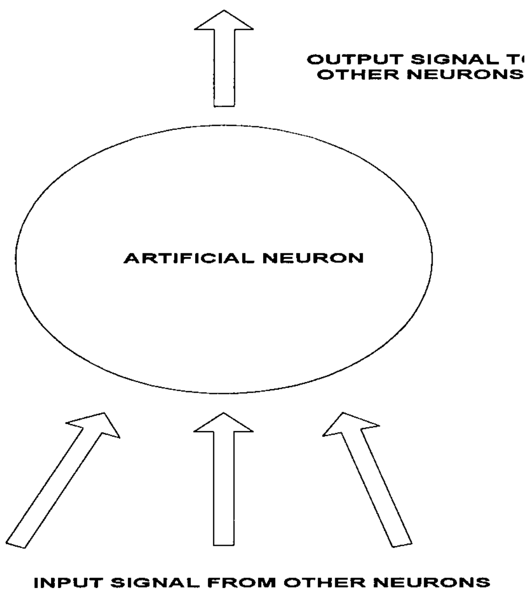


Fig. 2 Artificial Neuron scheme

The first phase of study concerns with the selection of the Neural Networks more suitable for diagnostic aims.

The second phase of the study deals with the problems linked with training.

The successive step of work concerns with the development of Neural Networks.

The following sections will describe, in full details, all activities carried out during this research.

2.-THE CONSIDERED NEURAL NETWORKS

As previously stated Neural Networks, are computer codes imitating the structure and the working of human brain.

The elemental unit of Neural Network is the artificial neuron. Just as the biological one it is connected with a lot of other similar elements.

There are many types of Neural Networks. The number of artificial neurons, their arrangement in layers, the connections among them are elements useful for classifying the different types of neural networks.

The analysis of different types and the experience heaped-up during past studies suggested to consider Back Propagation Neural Networks (BPNN) and Adaptive Resonance Theory Neural Network (ART1-2).

The selected Networks differs for their architecture, for the storage of information about faults and for the procedure used for training.

3.-THE TRAINING OF NEURAL NETWORK

Training is the most important and critical activity carried out during Neural Network development because it concerns with important activities as:

- the calculations the values of the strength of the connections among the Network units;
- the clustering of the different patterns describing the fault effects.

There are two different type of learning: supervised and unsupervised, (3), (4), (11), (12). The former uses an iterative procedures and uses two sets of patterns: the input and the output one.

Each input patterns corresponds to an output pattern. During training for any input the Net evaluates output values. An error arises and its amount is used for updating the weights of connections among the neurons.

When training starts the values of weights are assigned randomly and the procedure continues until to the calculated pattern is equal to the actual one.

Unsupervised training deals with the recognition and storage of patterns in clusters. The only requirement for this activity is the similarity among patterns and there is not control on learning.

Obviously the training of a Neural Network starts when suitable patterns, are available.

The patterns used for diagnostic Nets contain information describing the effects of known faults on aircraft engine behaviour, So the patterns are formed by the variations

of thermodynamic and performance parameters of engine, its components and systems when there is an active fault.

The parameter variations are evaluated with respect to baseline values of a 'healthy' engine.

From a practical point of view each pattern is the replay of engine to a fault, i.e. the symptoms shown by the apparatus when a fault arises.

Different sources may furnish the necessary patterns for Network training: maintenance manuals, past experiences and engine simulation.

For this study both engine simulation codes and maintenance manuals gave the patterns used for training. As in previous papers also now matrices of influence, (13), (14) are used as sets of patterns suitable for training.

Both simulation codes and overhaul manuals furnished a lot of information useful for constructing the matrices of influence. For this aim were used the results carried out in the past for simulating the fault effects in gas turbine engines (15), (16), (17).

The study considered a large two spool separated flow turbofan engine. It has a low pressure compressor mechanically linked to the fan. The engine resembles the General Electric CF6.

The used matrix of influence has 13 rows and 9 columns. This means that Neural Nets use 13 different effects of faults (training patterns) and 9 engine parameters (input elements). Table 1 and 2 show the faults and the engine parameters respectively.

TABLE 1
THE CONSIDERED FAULTS

1. **Decrease of L.P.C. capacity**
2. **Decrease of H.P.C. capacity**
3. **Increase of H.P.T. capacity**
4. **Increase of L.P.T. capacity**
5. **Decrease of FAN efficiency**
6. **Decrease of L.P.C. efficiency**
7. **Decrease of H.P.C. efficiency**
8. **Decrease of H.P.T. efficiency**
9. **Decrease of L.P.T. efficiency**
10. **Increase of Hot Stream Exit Area**
11. **Increase of Cold Stream Exit Area**

TABLE 2
THE ENGINE PARAMETERS

1. **Thrust**
2. **Inlet Mass flow rate**
3. **Hot Stream Mass Flow Rate**
4. **Cold Stream Mass Flow Rate**
5. **By-Pass Ratio**
6. **Exhaust Gas temperature**
7. **High Pressure Shaft rotational Speed**
8. **Low pressure Shaft Rotational Speed**
9. **Engine Pressure ratio**

In the following the matrix and the patterns will be called ***'basic'.***

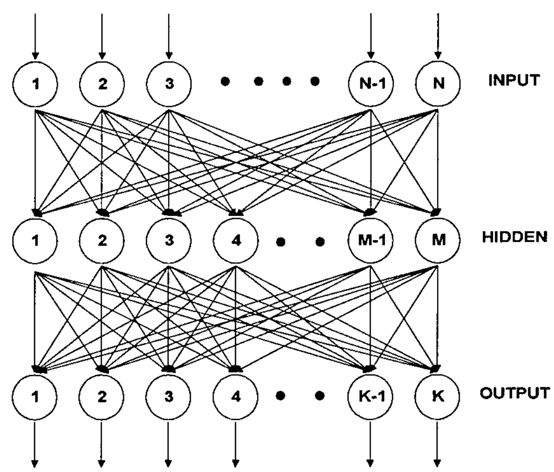
Experimental tests may furnish some of the used engine parameters while, Computer programs analyzing the results of experimental tests, give the other ones.

4.-THE DEVELOPED BPNNs

These Neural Networks derive their name from the particular procedure used for supervised training.

A general scheme of a BPNN is depicted in fig. 3.

Fig. 3 General scheme of a BPNN



In the past a lot of attention has been paid to these Nets, (18), (19), (20), (21).

The subjects of those studies concerned:

- the architecture of neural nets (number of hidden layers and number of their elements)
- the problems linked to the training (learning rate factor variation, activation functions, fault encoding, etc.)
- the tests on the robustness of developed Nets (the evaluation of their capability to recognize the right faults even if the patterns describing the engine behaviour are heavily noised and/or wrong).

The results allowed to obtain some solutions of different problems.

For instance the researches furnished suitable variation laws of learning rate factor during training.

Moreover the diagonal matrix proved to be the best way for encoding the faults, fig. 4.

1000000000000 fault 1
0100000000000 fault 2
0010000000000 fault 3
....
0000000000010 fault 12
0000000000001 faULT 13

Fig. 4 Unitary diagonal matrix for fault coding

The variable slope sigmoid proved to be the best activation function.

Finally the structure of a Neural Network, best fitting the requirements of both training and robustness, was found.

The general scheme of training procedure for the BPNN developed in the past is depicted in fig. 5. Each pattern is presented and learned by iteration. When a pattern is learned the successive one is considered up to its complete learning.

An epoch of training finishes, and the successive one begins, when all patterns, one by one, have been learned.

Finally the training stops when the Net is able to learn all patterns with only one iteration for each of them.

The necessary computer time depends upon the structure of Neural Network as well as on the number of patterns. This time ranges from few minutes to some days. Obviously the time is related to the use of a Personal Computer with a microprocessor Pentium II with 400-450 MHz clock.

The aim of this study wss the reduction of training time saving the robustness characteristics of BPNN.

The first step dealt with the change of learning procedure using again the diagonal matrix criterion for encoding the fault.

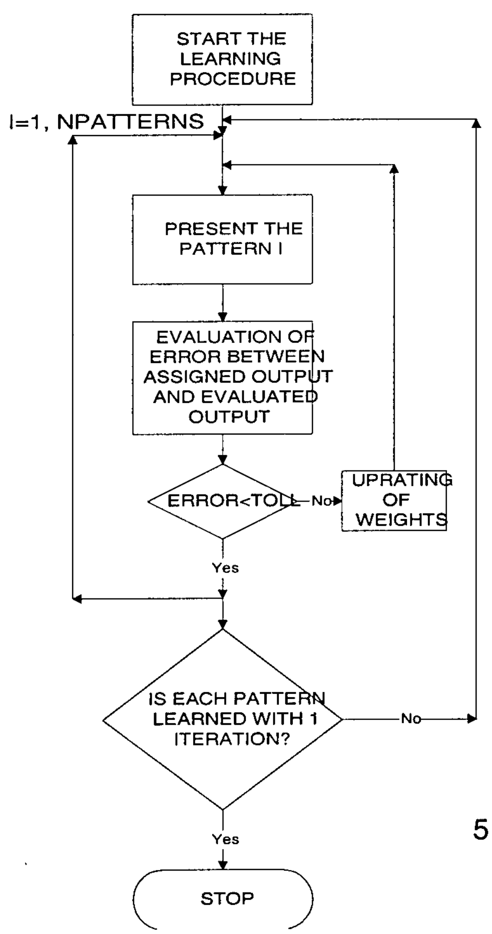


Fig. 5 The general old procedure for the training of BPNN

Fig. 6 shows the new training procedure. At the beginning of work the weights among the neurons are assigned randomly.

The Net considers the first pattern only one time. The comparison between the exact and the calculated output furnishes an error and this is used for updating the weights. Then the Neural Network considers the second pattern, evaluates the error, changes the weights and considers the

successive pattern.

When all patterns have been considered, one time each, the epoch finishes and the global error is evaluated.

The problem of this phase was the evaluation of the error value necessary for stopping the learning procedure.

Different values were used, i.e. 0.1, 0.05, 0.01, 0.001 and the capability of Neural Network to learn all patterns is used

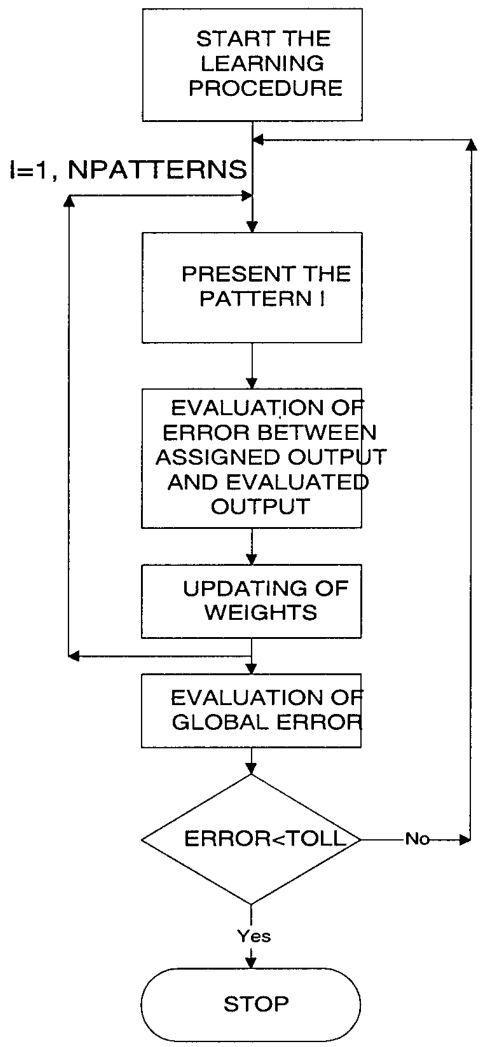


Fig. 6 The general new procedure for the training of BPNN

for selecting the value best fitting the requirement.

The calculations with the set of basic 13 patterns showed that some patters were quickly learned while others required lower tolerance. Fig. 7 shows the trend of one of the patterns versus the value of tolerance. Moreover fig. 8 shows the epochs necessary for reaching the assigned tolerance value.

This phase of study allows to select the tolerance equal to 0.001. Lower values did not give higher precision but lead only to higher computation times.

The training time required by the new procedure is less than the one necessary by the one used in the past even if the reduction is not so large.

The criterion for encoding the faults suggested a further step for improving the training time.

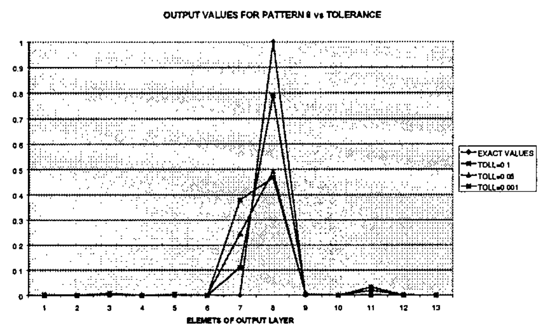


Fig. 7 The trend of a pattern for different values of tolerance

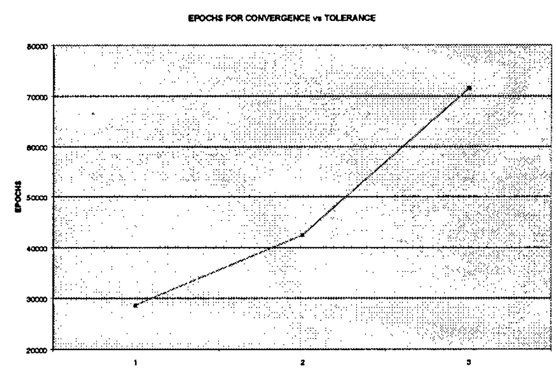


Fig. 8 The epochs necessary for reaching the desired tolerance

The diagonal matrix criterion requires that only one element of output layer is active for each fault, fig. 4. This element furnishes a value equal to 1 while the others must be equal to zero.

This means that, for each fault and set of symptoms, there is a sort of competition among the elements of output layer and there is only one winner.

This fact suggested to insert after of BPNN an other Net the MAXNET

It is a single layer Neural Network based on competition; it uses the criterion

'the winner takes all' and selects the element whose value is the higher one and rejects the other ones.

This important feature of MAXNET leads to the construction of a net formed by a BPNN followed by a MAXNET, fig. 9. This new Net, and the use of the new training procedure, permited to use higher tolerance, about 0.01 with a strong reduction of computational time. This is particularly important when there is an high number of patterns to learn. A suitable computation dramatically proved this aspect.

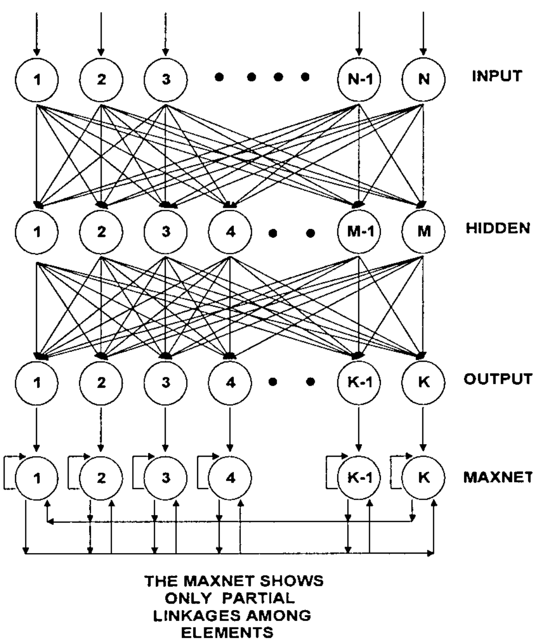


Fig. 9 The scheme of the new Neural Network (BPNN+MAXNET)

For this aim simulation codes furnished a matrix of influence containing 91 different faults or combinations of them.

The classical procedure required about 28 hours for convergence while the BPNN with MAXNET required only two hours.

The results of old procedure are very exact. The value of the only active element in the output layer is close to 1 but there are several oscillations toward the end of training. In other words the iterations for learning each pattern lower quickly but the convergence requires a very long time to be reached.

Moreover sometimes the Neural Network is unable to reach the convergence. It continues to oscillate indefinitely using few iterations for learning each pattern.

By using the MAXNET and the new procedure for learning it is possible to stop the learning even when there are more elements of output layer active. The training has already singled out the right one and the MAXNET selects it as the winner.

4.1-The robustness test

The new Net (BPNN+MAXNET) and the new procedure has dramatically proved to be very fast with respect to the past BPNN. But the question now is: what is its quality?

Therefore it was necessary to consider two Nets (BPNN and BPNN+MAXNET) for evaluating and comparing their robustness.

For this aim, the next step of study selected two Neural Nets with the following architecture: 10 input elements (9 parameters + 1 bias), 20 hidden elements, 13 elements in the output layer.

The two Nets were trained by the patterns of basic matrix of influence and the final weights of linkages among the neurons were stored.

The tests for robustness evaluation required the construction of three different sets of patterns. They derived from the basic 13 patterns by noising each of them 49 times in different manners.

This way the final sets contained 650 patterns. The difference among the sets of patterns and the criteria used for noising the basic ones are depicted in table 3.

TABLE 3
CRITERIA FOR CONSTRUCTING THE PATTERNS USED FOR THE ROBUSTNESS TESTS

Each pattern is noised:

1. **by randomly selecting 9 times a different element of pattern and adding to it a noise equal to ±2%, ±8%, ±15% of its basic value. The sign of noise is also chosen randomly;**
2. **by randomly selecting 9 time a different element of pattern and setting its value equal to zero;**
3. **by randomly selecting 31 times 5 different elements of basic pattern and adding to them a noise equal to ±20%, ±40%, ±80% of their basic values. Again the sign of noise is randomly selected.**

The final matrix of influence contains 13 groups each formed by 50 patterns, i.e.:

- 1 basic pattern;
- 9 patterns noised as in 1;
- 9 patterns noised as in 2;
- 31 patterns noised as in 3

The three matrices are related to amounts (±2%, ±20%), (±8%, ±40%), (±15%, ±80%) rspectively.

The two Neural Networks used the weights calculated by the training carried out with only 13 patterns and the calculation established how many new patterns were exactly recognized. The results are depicted in fig. 10 and they show that the new Neural Netwoek (BPNN+MAXNET) is more robust than the old one.

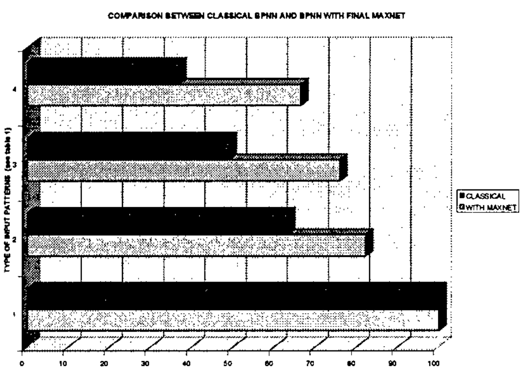


Fig. 10 Comparison of considered Neural Networks

The poor quality of old BPNN, is due to the strong noise that have affected the used sets of patterns.

The analysis of robustness of old BPNN may suggest an attempt for understanding the working of Net and for justifying its quality.

For instance it is interesting to study the behaviour of pattern 17. It is derived from pattern 1 and has been noised by putting the value 7^{th} element equal to zero. It is necessary to remember that the 7^{th} elements contains the variation of high pressure shaft rotational speed due to the decrease of low pressure compressor capacity. The pattern is not recognized by Net. Infact, fig 11, the corresponding output pattern has two elements whose values has the same order of greatness: element 1 and element 10. This means that the set of symptoms contained in the pattern 17 may correspond to fault 1 and to fault 10.

The analysis of these two the patterns, containing the symptoms of fault 1 and 10, helps to understand this strange behaviour.

Fig. 12 shows the structures of pattern 1 and pattern 10. They seem to be linked by a linear transformation. This fact and the introduced noise compel the pattern 17 to prefer both pattern 1 and 10 even if it is related to pattern 1 only.

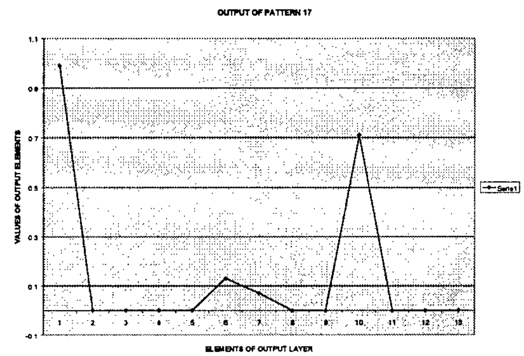


Fig. 11 Output values for pattern 17

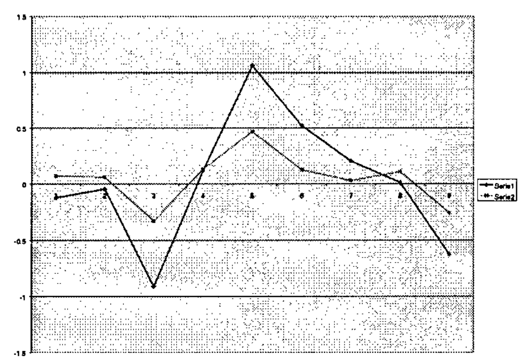


Fig. 12 the values of patterns 1 and 10

This is a characteristic way of Neral Network 'reasoning'. In other words by learning the pattern 1 the Net has acquired the ***'forma mentis'*** to learn easily also the pattern 10.

5-THE DEVELOPED ART

The Adaptive Resonance Theory Neural Networks are characterized by unsupervised learning. They are particularly suitable for clustering different patterns. There two types of ART: ART1 and ART2. The former uses binary input while the latter considers input patterns formed by continuous-value vectors.

In the past these nets have already been considered by the authors (19). This study presents the further applications of ART Nets for trouble-shooting and diagnostics of engines.

Again the basic matrix of influence may furnish the patterns necessary for training containing both binary and continuous-value elements.

Infact the matrix of inflòuence contains the trends of engine parameters due to arising known faults. So, by selecting a suitable encoding of trends, it is possible to obtain a significant set of patterns.

The encoding criterion, already used in the past, is depicted in table 4.

Table 4
Encoding of parameter trends

Increase behaviour: code 11
Decrease behaviour: code 00
Constant behaviour: code 01

This way the 13 patterns used for training are formed by 18 binary digit (each input pattern contains 9 elements).

The developed ART1 has 18 input elements and 13 clustering elements. The training reveals a problem due to the similarity of some patterns, fig. 13.

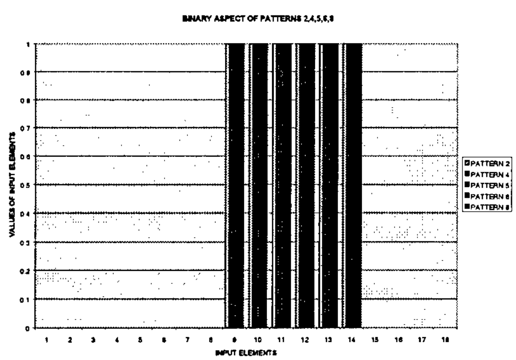


Fig. 13 The perfect similarity of some input patterns

This is a characteristics of behaviour of engine to faults. Infact different faults produce the same trends of engine parameters. The difference among patterns are due the effective values of shifting, fig. 14.

Anyway the uncertainty among symptoms and causes is a characteristic of the diagnostics of gas turbine engines as well as of other complex apparatuses.

The problem may be solved by using the probability that some symptoms are due to a fault.

This criterion is used also for ART1. Infact the each pattern, i.e. each fault, has been complete by its probability to happen. The probability has been encoded in 10 bits binary values so finally each pattern has 28 bits.

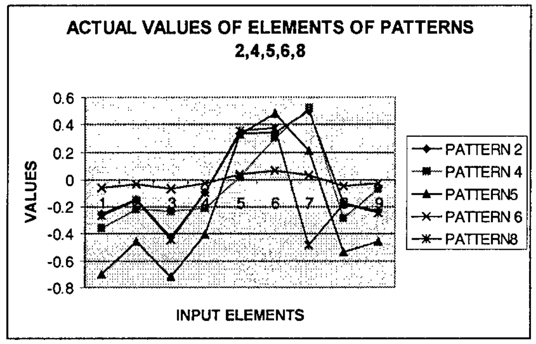


Fig.14 The actual values of patterns 2,4,5,6,8

This improvement allows the ART1 to store the binary symptoms of each fault in a different cluster avoiding the confusion.

Also for ART2 there is the same problem. This is due to the way the ART2 works. Infact the Net use the similarity among the patterns for storing them in the clusters.

Again the problem may be solved by using the probability of each fault to happen.

5.-CONCLUSIONS

The paper has dealt with BPNN and ART Nets for engine diagnostics and trouble shooting.

For BPNN the main target was the reduction of training time by assuring high level of Neural Network robustness. The variation of training criterion has proved to be effective by shortening the computer time.

The diagonal matrix criterion for encoding the faults suggested the use of another Neural Network after the BPNN. This is the MAXNET, a single layer Neural Network based on competition. Each time only one element of layer is the winner and has a values different from zero.

The use of this new Neural Networks (BPNN+MAXNET) as well as of the new

training procedure allow to reduce the time required for convergence. Infact, even if the training is not complete at the exit of BPNN, it is successfully completed by MAXNET.

The robustness test have proved that the BPNN+MAXNET is better than the old BPNN.

An attempt to explain the behaviour of the old BPNN and the reasons why it doesn't recognize exactly the patters is made.

At the present works are in full progress for testing Neural Networks working wiht a very large number of patterns (higher than 5000).

The work about ARTs has concerned the possibility to use the probability of a fault to happen. This way each set of symptoms, both binary and continuous-value, may be stored in a different cluster. This way the uncertainty between symptoms and faults may be avoided.

6.-BIBLIOGRAPHY

1)-s. CAMMARATA 'Reti Neuronali Una Introduzione all'"altra" Intelligenza Artificiale' Etaslibri Milano 1990

2)-M.H. HASSOUN 'Fundamentals of Artificial Neural Networks' The MIT press, Cambridge, Massachusetts, 1995

3)-S.I. GALLANT 'Neural Network Learning' The MIT press, Cambridge, Massachusetts, 1994

4)-L.FAUSETT 'Fundamentals of Networks Architectures, Algorithms and Applications' Prentice-Hall-1994

5)-D.M. HIMMELBLAU, R.W. BARKER, W. SUEWATANAKUL 'Fault Classification with aid of artificial neural network' IFAC/IMACS Symposium SAFEPROCESS '91 Baden-Baden, Germany 1991

6)-W.E. DIETZ, E.L. KIECH, M. ALI 'Jet Rocket engine fault diagnosis in real time' Journal of Neural Network Computing, 1 5-18, 1989

7)-M.A. KRAMER, J.A.LEONARD 'Diagnosis Using Back Propagation Neural Network - Analysis and Criticism' Computational Chemical Engineering, 14, 1323-1338, 1990

8)-S.R. NAIDU, E. ZEFIRIOU, T.J. McAVOY 'Use of Neural Networks for Sensor failure Detection in a Control System' IEEE Control System Magazine, 10, 49-55, 1990

9)-L.F. PAU 'Failure Diagnosis and Performance Monitoring' Marcel Dekker, New York 1981

10)-T. SORSA, H.N. KOIVO 'Application of Artificial Neural Networks in Process Fault Diagnosis' Automatica, Vol. 29, No. 4, pp843-849, 1993

11)-M.McCORD, W.T. ILLINGWORTH 'A Practical Guide to Neural Nets' Addison-Wesley Publishing Company, Inc. 1991

12)-J.A.FREEMAN, D.M.SKAPURA 'Neural Networks Algorithms, Applications and Programming Techniques' Addison-Wesley – 1991

13)-L.A. URBAN 'Gas Turbine Engine Parameters Interrelationships' 2nd edition Hamilton Standard UAC - 1969

14)-L.A.URBAN 'Gas Path Analysis Applied to Turbine Engine Condition Monitoring' AIAA paper 72-1082 December 1972

15)-G.TORELLA 'Problems and Use of Scaling Factors in the Numerical Simulation of jet Engines' ASME paper 90-GT-386 1990

16)-G.TORELLA 'Study on the Behaviour and Performance of Turbofan Engines with Faults in the Components' 1992 Engineering System Design and Analysis Conference - ASME PD-Vol.47-1 pp11-21, 1992

17)-G. TORELLA, G. LOMBARDO 'The Analysis of Influence of Component Performance Decay in Gas Turbines' AIAA paper 95-3031 1995

18)-G. TORELLA 'Neural Networks for the Diagnostics and Fault Detection of Gas Turbine Engines' - 7th European Propulsion Forum Aspects of Engine/airframe Integration – 10-12 March, 1999 – Pau France

19)-G. TORELLA, G. LOMBARDO 'Neural Networks for the Maintenance of Aeroengines' AIAA paper 95-2351 1995

20)-G. TORELLA, G. LOMBARDO 'Utilization of Neural Networks for Gas Turbine Engines' ISABE paper 95-7032, 12th International Symposium on Air Breathing Engines 10-15 September 1995, Melbourne, Australia

21)-G.TORELLA, G. LOMBARDO 'Artificial Intelligence Tools for the Maintenance of Turbofan Engines' ICAS-94 18-23 September, 1994 Anaheim, CA

Back